REMARKS

I. Introduction

In response to the Office Action dated October 2, 2007, claims 1, 8 and 15 have been amended. Claims 1-21 remain in the application. Re-examination and re-consideration of the application is requested.

II. Prior Art Rejections

A. The Office Action Rejections

In paragraph (5) of the Office Action, claims 1-21 were rejected under 35 U.S.C. §102(e) as being anticipated by Cook, U.S. Patent No. 6,631,360 (Cook).

Applicants' attorney respectfully traverses these rejections.

B. The Applicants' Claimed Invention

Independent claims 1, 8 and 15 are generally directed to creating a customer promotion response model for use in customer relationship marketing. Claim 1 is representative and comprises the steps of:

(a) defining an input data set for the response models, wherein the input data set is comprised of one or more Analytic Variables that include both primitives that are base variables and conditions that are predicates, aggregates or other functions that describe how the Analytic Variables are derived from operational data, and wherein the Analytic Variables are subdivided into independent and dependent variables;

(b) splitting the input data set into a test sample and a validation sample;

(c) identifying related independent and dependent variables using the test sample;

(d) identifying a Transformation Type for each of the identified related independent and dependent variables;

(e) estimating a Coefficient for each of the identified related independent and dependent variables;

(f) generating a Model Equation for each of the identified related independent and dependent variables using the identified Transformation Type and estimated Coefficient;

(g) validating the generated Model Equation by applying it to the validation sample; and

(h) scoring customers retrieved from a database stored in the computer using the validated Model Equation as a customer promotion response model for use in customer relationship

marketing.

C. The Cook Reference

Cook discloses a computer-implementable method of selecting which engine of a plurality of inference engines to use to predict the categories into which individuals fall, such as buyer/non-buyer, and produce forecast reports based on the predictions. Training (known) sample data that categorizes individuals based on the individual's profile is sequentially applied to multiple inference engines to determine which engine is best based on a desired objective. Then, a classifier associated with the selected engine is used to analyze unknown sample data, create category predictions and produce forecast reports based on the predictions.

D. The Applicants' Claims Are Patentable Over The Reference

Applicants' invention, as recited in independent claims 1, 8 and 15, is patentable over the Cook reference, because the claims recite a specific combination of limitations not found in the Cook reference.

The Office Action, however, asserts that Cook teaches all the elements of the independent claims, as well as all the elements of the dependent claims:

> Claims 1-21 are rejected under 35 U.S.C. 102(e) as being anticipated by Cook (US 6,631,360).
>
> Claim 1, Cook teaches:
>
> A computer-implemented method of creating customer promotion response models for use in customer relationship marketing, comprising.
>
> (a) defining an input data set for the response models, wherein the input data set is comprised of one or more Analytic Variables that include both primitives (see col 9, lines 35-45; col 12, lines 5-30; "data source, such as buy or no buy data") and conditions that describe how the Analytical Variables are derived from operational data (col 12, lines 5-30; categories of said data source), and wherein the Analytic Variables are subdivided into independent and dependent variables (see col 12, lines 17-22);
>
> (b) splitting the input data set into a test sample and a validation sample (see col 10, line 55 - col 11, line 20);
>
> (c) identifying related independent and dependent variables using the test sample (see col 12, lines 5-45);
>
> (d) identifying a Transformation Type for each of the identified related independent and dependent variables (see col 11, lines 20-65 "estimated density function");

(e) estimating a Coefficient for each of the identified related independent and dependent variables (see col 14, lines 55-65 "each element in a decision array there is a gain or loss");

(f) generating a Model Equation for each of the identified related independent and dependent variables using the identified Transformation Type and estimated Coefficient (see col 13, lines 5-45 "Gaussian Density function");

(g) validating the generated Model Equation by applying it to the validation sample (see col 11, lines 5-20 "calibration"; and

(h) scoring customers retrieved from a database using the validated Model Equation as a customer promotion response model for use in customer relationship marketing (see col 11, lines 50-67).

* * *

Response to Arguments

4. Applicant's arguments filed 07/13/2007 have been fully considered but they are not persuasive. The Applicant argues that Cook does not teach "defining an input data set for the response models, wherein the input data is comprised of one or more Analytical Variables that include both primitives and conditions that describe how the Analytical Variables are derived from operational data and wherein the Analytical variables are subdivided into independent and dependent variables". The Examiner answers that Applicant's specification page 6 defines said limitation by mentioning that "primitive variables" are based variables in transaction data, such as "sales" and "condition variables" are simply the categories where said variables corresponds, such as "Department = Merchandise". Cook teaches using base variables data source, such as buy or not buy data and classifying said data in categories in order to forecast the buy/not buy response of users (see col 12, lines 1-30). Furthermore, Cook teaches that that data source may include independent (ie. profile features such as buy or not buy) and dependent variables (ie. category into which a profile individual falls) (see col 12, lines 10-30). Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The Applicant argues that Cook does not teach "splitting the input data set into a test sample and validation sample". The Examiner answers that Cook teaches identifying a data source (i.e. test sample) and a training sample (i.e. validation sample) (see col 12, lines 25-35). Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The Applicant argues that Cook does not teach "identifying related independent and dependent variables using the test sample". The Examiner answers that Cook teaches that the data source includes independent and dependent variables (see col 12, lines 15-25). Therefore, contrary to Applicant's claimed invention, Cook teaches Applicant's claimed limitation.

The Applicant argues that Cook does not teach "identifying a transformation type". The Examiner answers that Cook teaches probability density functions that results in normal or quadratic decision surfaces (see col 10, lines 1-10). Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The Applicant argues that Cook does not teach "estimating a coefficient for the identified related independent and dependent variables". The Examiner answers that Cook figures 12 and 13 teach estimating coefficients (i.e. density value) for each

independent and dependent variable of said graph. Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The Applicant argues that Cook does not teach "a model equation". The Examiner answers that Cook teaches a inference engine, which are algorithms that calculate how independent variables for a given category are distributed according to some probability density function (see col 10, lines 1-10). Therefore, contrary to Applicant's argument, Cook teaches a "model equation".

The Applicant argues that Cook does not teach "validating the generated Model Equation by applying it to validation sample". The Examiner answers that Cook teaches performing a calibration process to determine the accuracy of a forecast (see col 11, lines 5-20). Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed invention.

The Applicant argues that Cook does not teach "scoring customers retrieved from a database using a Model Equation". The Examiner answers that Cook figures 12 and 13 teach determining the relative density value (i.e. score) for each individual category, feature and category. Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

Applicant's attorney disagrees with this analysis.

1. *The cited portions of Cook do not teach or suggest "defining an input data set for the response models, wherein the input data set is comprised of one or more Analytic Variables that include both primitives that are base variables and conditions that are predicates, aggregates or other functions that describe how the Analytic Variables are derived from operational data, and wherein the Analytic Variables are subdivided into independent and dependent variables."*

The portions of Cook cited by the Office Action as teaching the limitations "defining an input data set for the response models, wherein the input data set is comprised of one or more Analytic Variables that include both primitives and conditions that describe how the Analytic Variables are derived from operational data, and wherein the Analytic Variables are subdivided into independent and dependent variables" are set forth below:

<u>Cook: col. 9, lines 35-45</u>

Initially, as shown by block 401, a training sample is set up. As will be better understood from the following description of an example of a training sample setup process, setting up a training sample involves defining and naming categories and identifying a source of data for each defined category, i.e., a source of data that contains profile feature information (i.e., data) regarding individuals that fall in the defined categories. The data source must associate the profile data with the categories. The training sample setup 401 also involves assembling the data into a predetermined data structure.

Cook: col. 12, lines 5-30 (actually, lines 5-28)

> FIG. 5 illustrates a training sample setup process 401 formed in accordance with the present invention. Initially, categories are selected 501. As noted above, selecting categories involves defining the categories and naming them, i.e., buyer/non-buyer, responder/non-responder, responder/non-responder/unsubscribe, sick/healthy, friend/foe, etc. Category names are normally entered into a computer system by a user via a graphical user interface (GUI), also called a dialog window. Next, for a selected category a data source is identified. The data source may be as simple as a manually preformatted file. Alternatively, and more likely, the data source is a source of data developed by profiling Internet customers. The data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls. The data may be collected, for example, by advertising a product to a selected group of potential purchasers whose profile is known to the advertiser. The buy or no-buy results, combined with the potential purchasers' profile features, creates the data source for the selected category, i.e., buy or no-buy. Next, a test 505 is made to determine if any more categories have been entered by the user. If so, the next category is selected and a data source is identified, which may be the same data source.

The above portions of Cook merely describe data that contains profile feature information regarding individuals that fall in the defined categories. However, nothing in the above portions of Cook in any way teach or suggest Analytic Variables that include both primitives that are base variables and conditions that are predicates, aggregates or other functions that describe how the Analytic Variables are derived from operational data. Indeed, nowhere can the limitations of Applicants' claims be inferred from this discussion of Cook.

The Office Action's assertion that Cook teaches these limitations because it shows the use of base variables in the data source, such as buy or not buy data, and the use of conditions, such as classifying the data in categories in order to forecast the buy/not buy response of users, is erroneous.

As noted above, Applicants' claims recite that conditions "are predicates, aggregates or other functions that describe how the Analytic Variables are derived from operational data." Classifying data in a category does not teach these limitations, because mere classification does not "derive" the data. Indeed, the classification in Cook is performed first, and then a source of data for each defined category is identified.

Because Cook does not teach or suggest Applicants' claimed Analytic Variables, Cook does not teach or suggest the remaining limitations of Applicants' independent claims. Moreover, the

cited portions of Cook do not teach or suggest other limitations of Applicants' independent claims, as set forth below.

2. *The cited portions of Cook do not teach or suggest "splitting the input data set into a test sample and a validation sample."*

The portions of Cook cited by the Office Action as teaching the limitations "splitting the input data set into a test sample and a validation sample" are set forth below:

> <u>Cook: col. 10, line 55 – col. 11, line 20</u>
>
> Returning to FIG. 4A, after the first inference engine is selected, a set of profile features are selected 409. This step is included so that independent variables (individual profile features) that are not different among categories can be eliminated. Preferably individual profile features are sorted based on standard statistics after controlling for multicolinearities. In addition to eliminating independent variables for which there is insufficient data for estimation, less significant individual profile features can also be eliminated if desired. The end result is one or more sets of profile features. At step 409 one set is selected.
>
> After the inference engine and set of profile features have been selected, a training process is conducted 411. An example of a training process formed in accordance with the invention is illustrated in FIG. 6 and described below. In general, during the training process, various probability density functions are estimated for the selected engine and a data structure containing unbiased density values is created.
>
> After the training process 411 is completed, a calibration process 413 is performed. An example of a calibration process formed in accordance with the invention is illustrated in FIG. 8 and described below. The calibration process creates a decision array in which are stored the results of classifying the individuals whose individual profile features were contained in the training sample. As will be better understood from the following description, the decision array compares an individual's true category to the category predicted by the selected inference engine. The decision array in combination with the estimated density function and density value data structure contain all the algorithms and parameters necessary for implementation of the selected engine.

> <u>Cook: col. 12, lines 5-30 (actually, lines 5-28)</u>
>
> FIG. 5 illustrates a training sample setup process 401 formed in accordance with the present invention. Initially, categories are selected 501. As noted above, selecting categories involves defining the categories and naming them, i.e., buyer/non-buyer, responder/non-responder, responder/non-responder/unsubscribe, sick/healthy, friend/foe, etc. Category names are normally entered into a computer system by a user via a graphical user interface (GUI), also called a dialog window. Next, for a selected category a data source is identified. The data source may be as simple as a manually preformatted file. Alternatively, and more likely, the data source is a source of data developed by profiling Internet customers.

> The data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls. The data may be collected, for example, by advertising a product to a selected group of potential purchasers whose profile is known to the advertiser. The buy or no-buy results, combined with the potential purchasers' profile features, creates the data source for the selected category, i.e., buy or no-buy. Next, a test 505 is made to determine if any more categories have been entered by the user. If so, the next category is selected and a data source is identified, which may be the same data source.

The above portions of Cook merely describe selecting a set of profile features as a training sample. However, nothing in the above portions of Cook in any way teach or suggest that the set of profile features in Cook is generated by splitting an input data set comprised of Analytic Variables into a test sample and a validation sample.

3. *The cited portions of Cook do not teach or suggest "identifying related independent and dependent variables using the test sample."*

The portions of Cook cited by the Office Action as teaching the limitations "identifying related independent and dependent variables using the test sample" are set forth below:

> Cook: col. 12, lines 5-45
>
> FIG. 5 illustrates a training sample setup process 401 formed in accordance with the present invention. Initially, categories are selected 501. As noted above, selecting categories involves defining the categories and naming them, i.e., buyer/non-buyer, responder/non-responder, responder/non-responder/unsubscribe, sick/healthy, friend/foe, etc. Category names are normally entered into a computer system by a user via a graphical user interface (GUI), also called a dialog window. Next, for a selected category a data source is identified. The data source may be as simple as a manually preformatted file. Alternatively, and more likely, the data source is a source of data developed by profiling Internet customers. The data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls. The data may be collected, for example, by advertising a product to a selected group of potential purchasers whose profile is known to the advertiser. The buy or no-buy results, combined with the potential purchasers' profile features, creates the data source for the selected category, i.e., buy or no-buy. Next, a test 505 is made to determine if any more categories have been entered by the user. If so, the next category is selected and a data source is identified, which may be the same data source.
>
> After the data sources have been identified, a training sample set is established 507. This involves downloading data from the data source(s) and assembling the data into a computer file, or set of computer files, in a specific format, and storing the files in a workspace, i.e., in temporary memory. After

> establishing a training set in this matter, the downloaded data is converted into a training data structure having a predetermined configuration and the training data structure is stored in memory 509. A suitable training data structure is illustrated in FIG. 11. The profile features 1111a, 1111b, 1111c . . . 1111n of each individual 1113 in each category 1115 are included in the training data structure. As illustrated in FIG. 4A and discussed above, after the training data structure has been created, selected features of individuals may be eliminated. See step 409, FIG. 4A.

The above portions of Cook merely describe setting up a training sample by defining the categories, identifying a data source for a selected category (where the data source must include both independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls), and then downloading data from the data source to establish a training set. Nothing in the above portions of Cook in any way teach or suggest that these functions in Cook relate to identifying related independent and dependent variables, which are Analytic Variables, using the test sample.

4. *The cited portions of Cook do not teach or suggest "identifying a Transformation Type for each of the identified related independent and dependent variables."*

The portions of Cook cited by the Office Action as teaching the limitations "identifying a Transformation Type for each of the identified related independent and dependent variables" are set forth below:

> <u>Cook: col. 10, lines 1-10 (actually, col. 9, line 56 – col. 10, line 10)</u>
> After the objective has been set, a first inference engine is selected at 407. As will be better understood from the following description, the invention is architected with Bayes Rule as a framework. This allows any "inference engine" to be formalized in the same context. Bayes Rule effectively says that for a particular individual observation, that observation should be assigned to the category to which the observation has the maximum probability of belonging. The values of the independent variables, i.e., the individual profile features, are used to calculate these probabilities using a variety of inference engines. The inference engines are, in effect, algorithms that make the assumption that independent variables for a given category are distributed according to some probability density function. The most accurate inference engine will typically be the one for which the data are most closely modeled by the assumed probability density function. The presently preferred probability density functions are (a) normal with equal variances among categories that results in a linear decision surface, (b) normal with unequal variances among categories that results in a quadratic decision surface, and (c) Parzen that results in a polynomial decision surface.

Cook: col. 11, lines 20-65 (actually, col. 11, line 20 – col. 12, line 4)

After the calibration process has been completed for the selected engine, a test 415 is made to determine if any more sets of features need to be processed for the selected inference engine. If so, the next set of features is selected and the training and calibration processes 411 and 413 are repeated. If no more sets of features need to be processed, the set of features for the selected engine that best meets the desired objective are selected 417. Then a test is made to determine if any additional inference engines are to be selected. If so, as shown by decision block 415, the foregoing process is repeated, i.e., another inference engine is selected 409, a set of features is selected 409, and the training process is performed 411, followed by the calibration process 413. The foregoing sequence is repeated until no more inference engines remain to be selected.

Preferably, as each inference engine is processed, the resulting decision array is analyzed during the calibration step to determine if the current inference engine is better than previously processed inference engines. If so, the array and the estimated density function for the current inference engine replace previously stored decision array and estimated density function data. If the current inference engine is not better, the previously stored decision array and the estimated density function data is retained and this data for the current inference engine is discarded. Thus, after the training and calibration processes are complete for all inference engines, the decision array and estimated density function for the best inference engine are stored.

After the best inference engine has been selected in the foregoing manner, a sample comprising individual observations for which category membership is unknown is identified. The unknown sample contains the same independent variables (individual profile features) as did the training sample and is set up 421 in generally the same manner as the training sample was set up 401. An example of an unknown sample setup process formed in accordance with this invention is illustrated in FIG. 9 and described below. Thereafter, each individual in the unknown sample is assigned to a category using the previously developed and stored estimated density function associated with the selected best inference engine. Each such assignment is called a prediction. The predictions are tallied and the tally adjusted for error rates determined by the decision array created during the calibration process described above. The result is a forecast. See block 423. Next, a test 425 is made to determine if another unknown sample is to be analyzed. If so, the foregoing steps are repeated. After all unknown samples have been examined, the user can determine 427 if the objective needs to be reset. If the objective needs to be reset, the objective is reset and the entire process is repeated. If not, the process ends.

The above portions of Cook merely describe the inference engines as algorithms that make the assumption that independent variables for a given category are distributed according to some probability density function, and that the best inference engine is determined, using the training sample, based on an estimated Gaussian density function. As described in Cook, the estimated Gaussian density function estimates the proportions of selected subpopulations in a larger population. However, the estimated Gaussian density function of Cook is not a Transformation Type, which is defined as a mathematical operation that provides the strongest association between

the identified related independent variable and the dependent variables. This is not the same function as performed by Cook's estimated density function. Indeed, nothing in the above portions of Cook in any way teach or suggest that these functions in Cook relate to identifying a Transformation Type for each of the identified related independent and dependent variables, which are Analytic Variables.

5. *The cited portions of Cook do not teach or suggest "estimating a Coefficient for each of the identified related independent and dependent variables."*

The portions of Cook cited by the Office Action as teaching the limitations "estimating a Coefficient for each of the identified related independent and dependent variables" are set forth below:

<u>Cook: FIGS. 12 and 13</u>

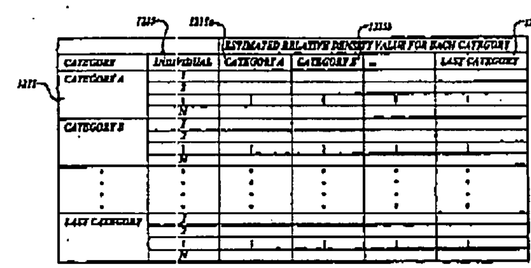

Fig. 12

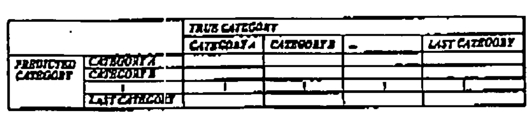

Fig. 13

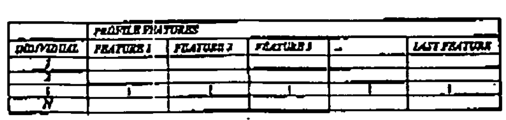

Fig. 14

Cook: col. 14, lines 55-65

> As will be readily appreciated by those skilled in the art to which this invention pertains, in the real world, each category will have associated benefits and costs. These benefits may be tangible, as in the case of dollars, or intangible, as in the case of goodwill. Thus, for each element of the decision array there is a gain or loss that can be assigned to each individual within that element. The net gain or loss for each element of the decision array is the individual gain or loss multiplied by the number of individuals assigned to that element. The objective function is thus the sum of these net gains or losses.

The above portions of Cook merely describe how each category will have associated benefits and costs. However, these category benefits and costs are not Coefficients, which are weights, for each of the identified related independent and dependent variables, which are Analytic Variables, found to be significant in predicting the likelihood of response. Nothing in the above portions of Cook in any way teach or suggest that these functions in Cook relate to estimating a Coefficient for each of the identified related independent and dependent variables.

6. *The cited portions of Cook do not teach or suggest "generating a Model Equation for each of the identified related independent and dependent variables using the identified Transformation Type and estimated Coefficient."*

The portions of Cook cited by the Office Action as teaching the limitations "generating a Model Equation for each of the identified related independent and dependent variables using the identified Transformation Type and estimated Coefficient" are set forth below:

Cook: col. 10, lines 1-10 (actually, col. 9, line 56 – col. 10, line 10)

> After the objective has been set, a first inference engine is selected at 407. As will be better understood from the following description, the invention is architected with Bayes Rule as a framework. This allows any "inference engine" to be formalized in the same context. Bayes Rule effectively says that for a particular individual observation, that observation should be assigned to the category to which the observation has the maximum probability of belonging. The values of the independent variables, i.e., the individual profile features, are used to calculate these probabilities using a variety of inference engines. The inference engines are, in effect, algorithms that make the assumption that independent variables for a given category are distributed according to some probability density function. The most accurate inference engine will typically be the one for which the data are most closely modeled by the assumed probability density function. The presently preferred probability density functions are (a) normal with equal variances among categories that results in a linear decision surface, (b) normal with unequal variances among categories that results in a quadratic decision surface, and (c) Parzen that results in a polynomial decision surface.

Cook: col. 13, lines 5-45

> As noted above, FIG. 7 illustrates a density function and density value calculating process 605 suitable for use in the process illustrated in FIG. 6 formed in accordance with the invention. First, a category is selected 701 by, for example, setting a pointer to the memory location of the data associated with the selection—in this case, the first category. Then, the density function for the category is estimated 703. More specifically, the parameters for the density function for the selected category are estimated from the training data structure (FIG. 11). For example, in the case where a Gaussian density function is used, the mean for each selected feature (FIG. 11) and the variance-covariance matrix for these features are estimated within each category (FIG. 11). These estimates become the parameter values in the estimated Gaussian density function for each category. In this estimated Gaussian density function, there exists a variable for each selected feature. The thusly created estimated density function is stored 705. Then, the estimated density function for the selected category is used to calculate an estimated relative density value for the selected individual in the selected category 707. More specifically, using the foregoing example, the values of the selected features are substituted for the variables in the estimated Gaussian density function and a scalar is obtained. The result is used to create a density value data structure, which is stored 709. Then a test 711 is made to determine if any more categories exist. If more categories exist, the process is repeated. As will be recalled, the process illustrated in FIG. 7 occurs after the training data structure has been updated by removing a selected individual from a selected category. Thus, the density value data structure is for a selected individual in a selected category with the n individuals' data removed. An example of a density value data structure is shown in FIG. 12. For each category 1211 an estimate of the likelihood that each individual 1213 will fall in each category 1215a, 1215b . . . 1215n is included in the data structure.

The above portions of Cook merely describe that a category is selected, the parameters for the density function for the selected category are estimated from the training data (in the case where a Gaussian density function is used, the mean for each selected feature and the variance-covariance matrix for these features are estimated within each category), and then the estimated density function for the selected category is used to calculate an estimated relative density value for a selected individual in the selected category (the values of the selected features are substituted for the variables in the estimated Gaussian density function and a scalar is obtained). However, nowhere does Cook describe a Transformation Type or a Coefficient, and consequently, Cook does not describe generating the same Model Equation as recited in Applicants' claims. Nothing in the above portions of Cook in any way teach or suggest that these functions in Cook relate to generating a Model Equation for each of the identified related independent and dependent variables, which are Analytic Variables, using the identified Transformation Type and estimated Coefficient.

7. *The cited portions of Cook do not teach or suggest "validating the generated Model Equation by applying it to the validation sample."*

The portions of Cook cited by the Office Action as teaching the limitations "validating the generated Model Equation by applying it to the validation sample" are set forth below:

> Cook: col. 11, lines 5-20
> After the training process 411 is completed, a calibration process 413 is performed. An example of a calibration process formed in accordance with the invention is illustrated in FIG. 8 and described below. The calibration process creates a decision array in which are stored the results of classifying the individuals whose individual profile features were contained in the training sample. As will be better understood from the following description, the decision array compares an individual's true category to the category predicted by the selected inference engine. The decision array in combination with the estimated density function and density value data structure contain all the algorithms and parameters necessary for implementation of the selected engine.

The above portions of Cook merely describe a calibration process using the training sample, but does not describe validating the generated Model Equation by applying it to a validation sample that is created by splitting an input data set into a test sample and a validation sample. Nothing in the above portions of Cook in any way teach or suggest that these functions in Cook relate to validating the generated Model Equation by applying it to the validation sample.

8. *The cited portions of Cook do not teach or suggest "scoring customers retrieved from a database using the validated Model Equation as a customer promotion response model for use in customer relationship marketing."*

The portions of Cook cited by the Office Action as teaching the limitations "scoring customers retrieved from a database using the validated Model Equation" are set forth below:

Cook: FIGS. 12 and 13

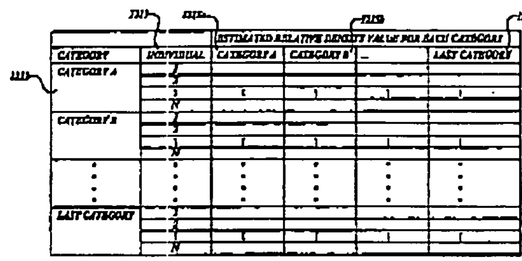

Fig. 12

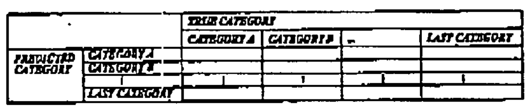

Fig. 13

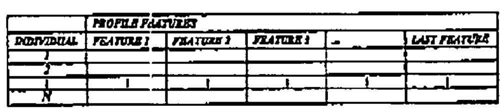

Fig. 14

Cook: col. 11, lines 50-67 (actually, col. 11, line 49 – col. 12, line 4)

After the best inference engine has been selected in the foregoing manner, a sample comprising individual observations for which category membership is unknown is identified. The unknown sample contains the same independent variables (individual profile features) as did the training sample and is set up 421 in generally the same manner as the training sample was set up 401. An example of an unknown sample setup process formed in accordance with this invention is illustrated in FIG. 9 and described below. Thereafter, each individual in the unknown sample is assigned to a category using the previously developed and stored estimated density function associated with the selected best inference engine. Each such assignment is called a prediction. The predictions are tallied and the tally adjusted for error rates determined by the decision array created during the calibration process described above. The result is a forecast. See block 423. Next, a test 425 is made to determine if another unknown sample is to be analyzed. If so, the foregoing steps are repeated. After all unknown samples have been examined, the user can determine 427 if the objective needs to be reset. If the objective needs to be reset, the objective is reset and the entire process is repeated. If not, the process ends.

The above portions of Cook merely describe using the estimated density function for a selected category to calculate an estimated relative density value for a selected individual in the selected category. However, as noted above, an estimated density function is not a Model Equation or Transformation Type, and the result from an estimated density function is not a Coefficient. Nothing in the above portions of Cook in any way teach or suggest that these functions in Cook relate to scoring customers retrieved from a database using the validated Model Equation.

9. Summary: Applicants' claimed invention is patentable over Cook."

In light of the above, Applicants' attorney submits that independent claims 1, 8, and 15 are allowable over Cook. Further, dependent claims 2-7, 9-14, and 16-21 are submitted to be allowable over Cook in the same manner, because they are dependent on independent claims 1, 8, and 15, respectively, and thus contain all the limitations of the independent claims. In addition, dependent claims 2-7, 9-14, and 16-21 recite additional novel elements not shown by Cook.

III. Conclusion

In view of the above, it is submitted that this application is now in good order for allowance and such allowance is respectfully solicited.

Should the Examiner believe minor matters still remain that can be resolved in a telephone interview, the Examiner is urged to call Applicants' undersigned attorney.

Respectfully submitted,

GATES & COOPER LLP
Attorneys for Applicants

Howard Hughes Center
6701 Center Drive West, Suite 1050
Los Angeles, California 90045
(310) 641-8797

Date: January 2, 2008

By:
Name: George H. Gates
Reg. No.: 33,500

GHG/

G&C 30145.426-US-01